Ph.D. Title Proposal

on

Design and Development of Generative Model for Multiobject Deepfake with Convolutional Neural Network

Submitted in partial fulfillment of the requirement for
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by

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PROPOSAL FOR TOPIC APPROVAL TO BE SUBMITTED TO THE UNIVERSITY OF MUM- BAI FOR THE DEGREE OF **Ph.D. (SCIENCE AND TECHNOLOGY)** IN THE SUBJECT OF **COMPUTER ENGINEERING**

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Statement by the Candidate

I wish to state that the work embodied in this synopsis titled "**Design and development of Generative Model for Multiobject Deepfake detection with Convolutional Neural Network** " forms my own contribution to the work carried out under the guidance of Dr. Amiya Kumar Tripathy at the Shah and Anchor Kutchhi Engineering College. I declare that this written submission represents my ideas in my own words and where others ideas or words have been included, I have adequately cited and referenced the original sources. I also declare that I have ad- hered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission.

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Introduction

Deep-fake technology is a revolutionary technology that has taken the digital world of content creation and manipulation to an all-new level through utilizing sophisticated Intelligence System (AI) or machine learning mechanisms. By virtue of the deep neural networks, which include the Generative Adversarial Networks (GANs), deepfakes can create photorealistic synthetic content-including portrayal, videos, together with sounds-that approximate actual media content. This presents major ramifications for many industries, inclusive of amusement, coaching, and cybersecurity. Generative Adversarial Networks (GANs) found a way through which deepfake works; in this model of deepfake, duet neural networks, namely the generator and discriminator, have being made to oppose each other. While the generator synthesized data, the values provided by the discriminator told how fake the Japanese synthesized data are. Thus, the outputs are refined again and again. With latest modifications comes modified architectures from DCGANs to GANs based on Transformers that allowed to produce images of a higher quality and diversity in their synthesized types. This has led to facilitate even more sophisticated deepfakes becoming far more convincing[1]. While early deepfake applications primarily focused on the manipulation of single objects, the emergence of multi-object deepfakes—wherein multiple entities within a single frame are altered—has presented new challenges and opportunities. Generation of complex content like these would require sophisticated models capable of doing justice to complex spatial relationships while ensuring that every manipulated element runs in sync. Convolutional Neural Networks (CNNs) have proven vital in this respect, providing powerful frameworks for capturing spatial hierarchies of visual data. Their layered architecture does allow for abstraction at several levels for feature extraction, making the task of dealing with multiple objects and complex scenes easier.In spite of the advancements regarding deepfake generation, the biotic relationship between creation and detection remains a fluid area of study. Developing models which are increasingly sophisticated in the deepfake creation process has been matched with a heightened sophistication of their corresponding techniques for detecting manipulated content. This ongoing "tug-of-war" requires evermore research into producing better quality deepfakes while working alongside the understanding and limitation of potential misuse. In this regard, researchers have been exploring various approaches, incorporating into the whole of multichannel data and the investigation of causal AI mechanisms to improve the detection and understanding of deepfakes[2].This study purpose to design and flourish a CNN-based generative model for making multi-object deepfakes. It takes within pursuit the specifics that arise upon manipulating multiple entities residing on a frame. The results of this work likely to have a wide impact implications for digital content creation, virtual reality, and cybersecurity, where the generation and detection of intricate synthetic media are become increasingly pertinent. Furthermore, the understanding of the mechanisms of multi-object deepfake generation would contribute to the formulation of more robust detection methods which in the larger debate on media authenticity and security.

Literature Review

Lu et al. (2024) proposed an assessment framework for this purpose, to evaluate deepfake detection models Subjected to real-life distortions, the improvement in existing approaches to deepfake detection benchmarking, the authors investigate four deepfake detection models, namely, Capsule-Forensics (CNN + Capsule Networks), XceptionNet (CNN-based classifier), SBIs (Self-Blended Images for synthetic training), and UIA-VIT (Vision Transformer-based detector). The framework systematically tests these models against real-world distortions like image/video compression, noise, blurring, resizing, and enhancement. A Stochastic Degradation-Based Augmentation (SDAug) method is introduced where random distortions are applied to improve model robustness. The research is also introduced through a Python toolbox for benchmarking that automates the evaluation through the use of TorchVision's Transforms module. The findings show that real-world distortions can significantly degrade the performance of deepfake detectors, and the CNN-based models (Capsule-Forensics, XceptionNet) are particularly sensitive to compression and noise. UIA-VIT (transformer-based model) shows better generalization, but still faces challenging issues. The proposed SDAug approach leads to improved robustness by the model against modalities particularly common in real-world scenarios [3].

Additionally, Soudy et al., 2024 proposed a deep-learned method for altered photo or video detection using Convolutional Neural Network (CNN) and Convolutional Vision Transformers (CViT). The process consists of three main areas: preprocessing, detection, and prediction phases. The pretreated phase involves frame elicit, face observation, calibration, and trimming. The CNNs are the first to be adopted, in the detection phase, in eye and nose feature detection, while a combination of a CNN and a Vision Transformer model is used by scanning a person’s face. The final divination uses a bulk voting technique to combine arise from different models; the unification relies on the extreme majority win. The method was trained on the FaceForensics++ and DFDC datasets, using accuracy, precision, recall, and F1 score for evaluating the performance. Experimental results substantiate that the CNN model achieved 97% accuracy while CViT objected to 85% accuracy on the FaceForensics++ dataset. This study proves effective by providing sufficient opportunity with CNN-based methods against real-world scenarios of deepfake detection when compared to Vision Transformers which, despite suffering from difficulties in performance, have a preferential advantage in their ability to learn complex patterns in facial images.

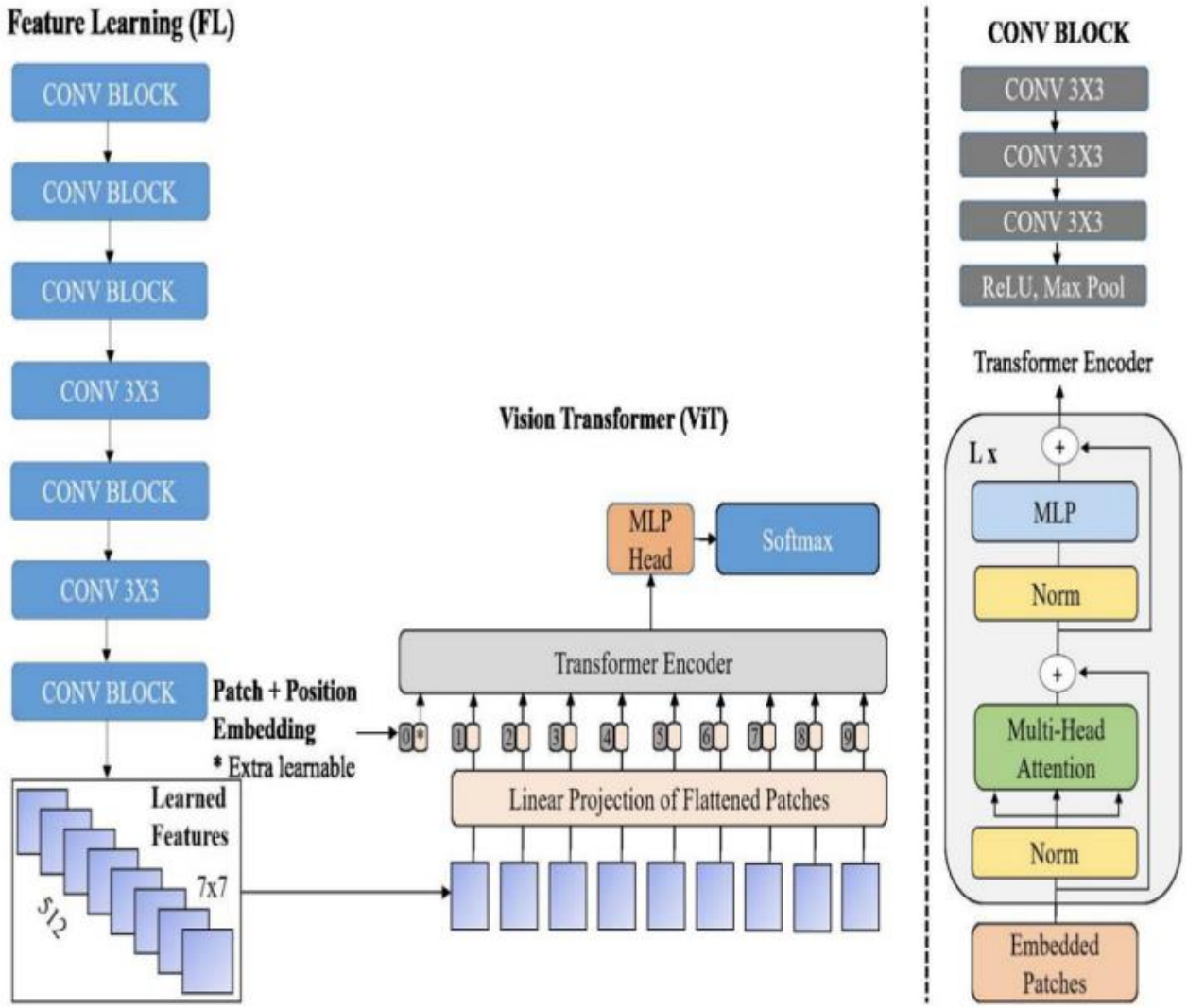


Figure 1: Convolutional Vision Transformer Model

In 2024, Gandhi et al. proposed a fusion, multimodal deepfake detection framework that operates through both visual and auditory analysis to optimize performance. The system extracts nine facial features based on Haar Cascade and FaceMesh and uses machine learning models (Decision Trees, Random Forests, and XGBoost) and deep learning models (ANN, CNN, and VGG19) for their classification. For the audio analysis, mel-spectrograms and MFCC features are extracted and classified using CNN and VGG19, achieving 98% accuracy. Multimodal fusion combines the outputs of the audio stream and video stream, and if any one modality is fake, the content is classified as deepfake. This framework achieved 94% accuracy, outperforming unimodal models. The study shows that multi-modal fusion improves robustness against deepfake manipulations, therefore making detection reliable over varying datasets and scenarios.[5]

In 2024, Yan et al. proposed a wide reaching deepfake detection dataset, DF40, which seek to enhance the

performance of deepfake detection on diverse deepfake methods. This dataset has deepfakes using 40 practices, including, among others, face-swapping, face-reenactment, full-face synthesis, and face editing, thus addressing the limitation of the outdated existing datasets. The study reviews the performance of eight detection models within four evaluation protocols, performing over 2,000 experiments to benchmark the performance. Key study techniques included deep learning detection models (Xception, CLIP, and SRM) and domain adaptation techniques for testing cross- forgery generalization. From the investigations, the modern state-of-the-art detectors had significant difficulties dealing with the recent deepfakes, particularly in the case of cross-domain settings, while pre-trained models such as CLIP can outperform classical deepfake detection architectures. This study highlighted the need for more feeble detection approaches capable of leveraging changes to deepfake techniques, allowing further advances in relation to the algorithm and resulting better applicability of the detection externally[6].

Wodajo et al. proposed GenConViT, which is a generative convolutional vision transformer model for deepfake video detection. The architecture consists of ConvNeXt and Swin Transformer for extracting features and integrated Autoencoder and Variational Autoencoder techniques to learn the dormant data distribution. The analysis was carried out in three steps: i.e., preprocessing for face detection and alignment; feature extraction using ConvNeXt and Swin Transformer; and finally, classification. The model was uphill and tested on datasets DFDC, FaceForensics++, DeepfakeTIMIT, and Celeb-DF (v2) to achieve 95.8% accuracy and AUC of 99.3% on average. It has shown a clear generalization across datasets than other models for deepfake detection. It presents evidence that combined use of visual artifacts and latent features improves deepfake detection accuracy and makes them more robust to different manipulations.

Johnson et al. presented an ensemble-convolutional neural network-based deepfake detection model using periocular data extracted from a masked face. The method combines SIFT and HOG using convolutional neural networks in feature extraction to obtain better classification results. The dataset used are DeepFakeDetection, FaceForensics++, FaceSwap, and NeuralTextures, from which periocular images were extracted using MTCNN face detection. The ensemble combines outputs from CNN, SIFT, and HOG feature extractors via a stacked architecture. The model was trained on a 90/10 train-test split and finally analyzed through measures of accuracy, precision, recall, F1 score, and ROC-AUC. The results indicate that the ensemble model is capable of achieving an accuracy of 98.9% on the DeepFakeDetection dataset, over individual models. The study shows that deepfake identification using periocular-based detection holds prowess in masked scenarios with clearer edge and enhancement to feature-based detection via SIFT and HOG.

Giatsoglou et al. (2023) discussed ensemble deep-like methods for deepfake face manipulation detection focusing on improving robustness and generalization. The research examined multiple ensemble architectures using

EfficientNet-B0 CNN models trained on the FaceForensics++ dataset with MTCNN employed for face detection. Four ensemble designs were investigated: binary detection ensemble, multiclass attribution ensemble, one-manipulation-vs-real ensemble, and one-manipulation-vs-rest ensemble. The model was trained using the binary cross-entropy and multiclass cross-entropy loss with the Adam optimizer and tested on still uninformed datasets, like Celeb-DF and DFDC. Results show that all ensemble approaches outperform individual model results, while one-manipulation-vs-others-one produced the best accuracy in high-quality deepfakes. However, there is a low performance when it comes to cross datasets, which reiterates the need for more diversified training data to boost generalization [9].

In 2024, Bakliwal et al. correlated a hybrid model of deepfake detection that integrates 2D and 3D CNNs to gain improved accuracy. The 2D CNN model employs EfficientNetB4 with attention (Attention2D) to consider important facial regions, while the 3D CNN model (Ensemble3D) captures spatiotemporal inconsistencies of deepfake videos. The system leveraged Voting Ensembles and Adaptive-Weighted Ensembling, assigning more priority to 3D model outputs, as they perform better in terms of analyzing temporal patterns. The model included DFDC dataset training and face extraction done using BlazeFace, while the evaluation was done through the use of Log Loss and AUC metrics. The hybrid 2D-3D model was shown to outstrip individual CNN models, with AUC values reaching 89.69%, evidence that it is effective. The advantages of combining spatial and temporal analysis for robust deepfake detection were noted, although greater computational costs form a limitation [10].

Salvi et al. (2023) proposed a multimodal deepfake detection framework that combines audio and visual modalities to withstand synthentic media. Time-aware neural network analyzes the audio-visual features, hence enhancing the detection performance. An important novelty is that the model is trained on separate datasets of monomodal deepfakes, be it visual-only or audio-only deepfakes, thus eliminating the need for multimodal datasets during training. The study evaluated several fusion techniques to combine visual and audio modalities effectively. The framework was tested upon state-of-the-art multimodal deepfake datasets and demonstrated excellent generalization capabilities to unseen data. Results illustrate that the multimodal approach outperforms monomodal detection systems even when trained on separate datasets. The research points out the incongruence between audio and visual aspects as potential points for the detection of deepfakes. In real-life projects, such an approach could lead to better robustness, as actual deepfake production tends to have discrepancies between and among various media modalities [11].

Xiong et al. (2025) set forth BMNet, a deepfake detection model that integrates Bi-Directional Long Short-Term Memory (BiLSTM) networks and Multi-Head Self-Attention (MHSA) mechanisms to enhance spatiotemporal feature extraction. This method processes video frames on the basis of detection of 68 facial landmarks using the Dlib face detector. These landmarks are subsequently passed through BiLSTM for temporal abstraction. The

MHSA module makes the features representation better by emphasizing different regions of an image within the same feature map and hence provides better detection of subtle forgeries. The model was trained and evaluated on the datasets: UADFV, FaceForensics++, Celeb-DF, and DFDC, achieving: 95.54% accuracy on FaceForensics++, 92.18% on UADFV, 80.20% on Celeb-DF, and 84.72% on DFDC. Results validated that BMNet outperformed traditional CNN-based methods by a great margin when detecting high-fidelity deepfake videos. The study indicates that the combination of temporal models with attention modeling played an important role in performance improvement with respect to deepfake detection, which made BMNet relatively resilient to variations in datasets and levels of compression [12].

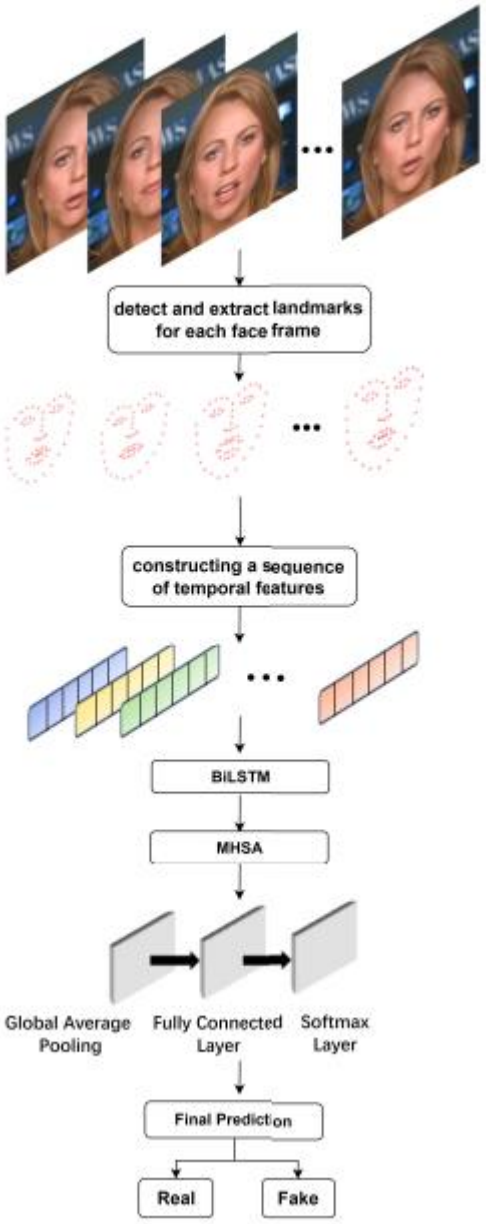


Figure 2: BMnet Framework for Deepfake Detection

Babu et al. (2025) proposed a multi-path Convolutional Neural Network model with a Convolutional Block Attention Mechanism developed fur deepfake detection. The model contains ResNet50, DenseNet121, and InceptionResNetV2, which are intended for improvement of feature extraction. Feature reuse is allowed by ResNet50, new feature representations were captured by DenseNet121, and residual connections were incorporated to InceptionResNetV2, aiding in learning. By each path of the CNN, the CBAM module can be applied to sharpen attention to important channel-based and spatial features, augmenting model accuracy. The system deals with face-cropped images extracted from the DFDC dataset, using HOG + Linear SVM-based face detection. The model was trained, actually, for 20 epochs and attained an accuracy of 94% with an F1-score of 0.939, outperforming existing deepfake detection models. CBAM improves the extraction capability, so detecting manipulated media might be better, and this indicates the advantage of attention-based mechanisms for deepfake detection.

Liang et al. (2023) suggested HTNet-a deepfake detection model, which leverages a two-stream network with hierarchical supervision for improved detection accuracy. The two-stream framework has a spatial stream to capture semantic features from RGB images and a frequency stream to analyze frequency-domain DCT artifacts. It leaves low-quality deepfake images with artifacts based on the frequency, despite compression. Using hierarchical supervision, the model coarsely-to-finely classifies deepfakes. First, it tells the images apart based on whether they are real and fake, followed by the classification of fake into four manipulation categories. This model was trained and evaluated over the FaceForensics++, Celeb-DF, and DFDC datasets with 86.68% accuracy for the low-quality FaceForensics++ videos, winning against existing deepfake detection models in cross-dataset evaluations. Combining frequency domain features with hierarchical classification tends to give HTNet robustness in practical real-world contexts for deepfake detection.

Bakliwal et al. have introduced a hybrid 2D and 3D Convolutional Neural Network-based deepfake detection model with better accuracy. The 2D CNN model is based on EfficientNetB4 with an Attention2D mechanism, which helps extract features. The 3D CNN model captures spatiotemporal incongruities within deepfake videos. The ensemble combines features in Voting Ensembles and Adaptive Weighted Ensembling, with 3D CNN-based outputs being rated highly since they are best for recognizing patterns in time. The model was trained and tested on the DFDC dataset and provided data with face detection through BlazeFace and various data augmentation strategies. The hybrid model, combining 2D and 3D CNNs, was evaluated on Log Loss and AUC and outperformed the single CNN models with an AUC of 89.69%, signifying robustness. It was concluded that spatial and temporal features were conjointly essential for deepfake detection but required higher computational resources [10].

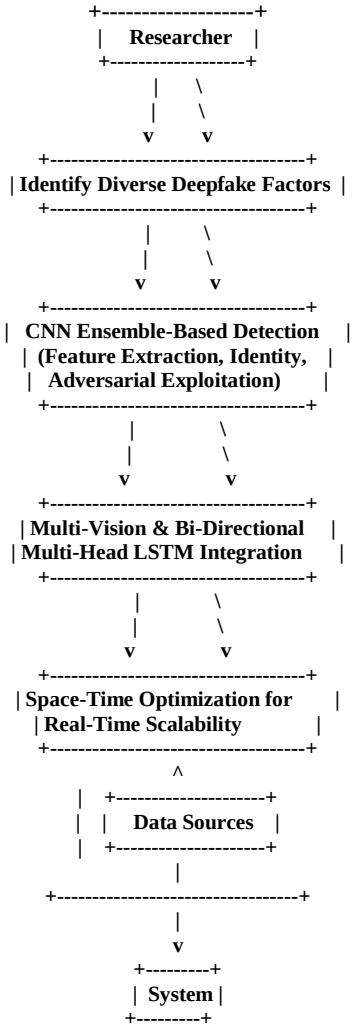
Wodajo et al. represented GenConViT-a Generative Convolutional Vision Transformer model-and it was used

and tested for deepfake video detection. The model incorporates ConvNeXt and Swin Transformers for feature extraction, AE, and VAE to learn the latent distributions. The system does its work in three main steps: video preprocessing (face detection and alignment), feature extraction (ConvNeXt + Swin Transformer), and classification. The model was trained and tested on the DFDC, FaceForensics++, DeepfakeTIMIT, and Celeb-DF (v2) datasets, achieving 95.8% accuracy and an AUC value of 99.3%. In comparison with other existing models, GenConViT exhibited higher generalization across different datasets. It has been shown that visual artifacts combined with latent feature analysis do improve the accuracy of deepfake detection, making the model much more robust to advanced manipulations [7].

Spatiotemporal Inconsistency Learning (STIL) framework proposed by Gu et al., in 2021, dedicates a mention to the inconsistencies of both the spatial and temporal variabilities present within a deepfake video. Comprising three main modules: (1) a Spatial Inconsistency Module (SIM) to identify special forgery patterns, (2) a Temporal Inconsistency Module (TIM), for capturing unnatural transitions across frames, and (3) an Information Supplement Module (ISM), which improves representation by fusing the spatial and temporal features. Two-dimensional CNN architectures for processing video frames were combined into ResNet-based backbones by STIL. The model was evaluated and trained on FaceForensics++, Celeb-DF, DFDC, and WildDeepfake datasets and showed state-of-the-art performance across both intra-dataset and cross-dataset evaluations. Results showed that modeling temporal inconsistency improves deepfake detection, especially in low-quality forgeries. The study shows that the combination of spatial artifacts with between-frame inconsistencies-enhancing robustness is significant and makes STIL viable in real-life deepfake detection scenarios.

Research Hypothesis

- Identification of diverse factors responsible for deepfake techniques would therefore assist in better detection.
- The proposed CNN ensemble-based network will help improve the accuracy of multi-object deepfake detection by featuring extraction, identity-preservation, adversarial exploitation, and so on.
- The integration of multi vision networks shall enhance the performance of the bi-directional multi-head LSTM model.
- Optimization using space time techniques will make the model scalable to real-time applications.



System Flow Chart

Aims & Objective

1. To investigate the factors that influences the deepfake detection methodology.
2. To Design & Develop Generative Model for Multi-Object Deepfake with CNN Ensemble based Granulated Neural Network.
3. To Analyze the effectiveness of multi-supervision networks in reinforcing the bidirectional multi-head LSTM for the detection of deepfakes.
4. To Optimize the model with Spatiotemporal techniques towards robustness and scalability.

Materials & Methods

This comparative study analyzed the factors influencing deepfake detection using datasets such as FaceForensics++, Celeb-DF, and DFDC. The various detection techniques evaluated included CNN, Vision Transformers, and RNN-based models. Key performance metrics were analyzed under different perturbations, including accuracy, F1-score, precision-recall, and AUC-ROC.

A CNN ensemble-based generative model was devised to strengthen deepfake detection. The ensemble consisted of ResNet, EfficientNet, DenseNet, and InceptionNet using Granulated Neural Network (GNN) for active feature extraction. Data augmentation was performed with GAN-generated synthetic deepfakes to enhance generalization.

To learn a multi-supervision network, Bi-MH LSTM was integrated with CNN-based feature extractors. Multi-supervision techniques offered hierarchical learning at different layers, enhancing the sequential representation of features. Through the attention mechanism in multi-head LSTM, temporal dependencies among frames were strengthened.

For optimization, Spatiotemporal Inconsistency Learning was adopted. This included Spatial Inconsistency Module (SIM), Temporal Inconsistency Module (TIM), and Information Supplement Module (ISM), fine-tuning the model with the AdamW optimizer with adaptive learning rates and validating it in a cross-dataset evaluation. Other techniques such as data augmentation, adversarial training, and domain adaptation improved robustness.

Finally, the model was evaluated under multiple real-world scenarios, including different frame rates, varying compression levels, and occlusions. Results showed better scalability and generalization compared to existing state-of-the-art deepfake detection models. Extensive evaluation awarded the model with resilience against advanced deepfake manipulation techniques.

Expected Results/Outcome

- In-depth comprehension of the major roles played by target factors while gauging for really flawless detection models able to stand a lot of making for superior and accurate mechanisms for finding deepfakes.
- Most efficient generation-based model that integrates CNN ensemble and Granulated Neural Network for enhanced multi-object deepfake detection with higher accuracy in extracting and classifying features.
- To improve the accuracy of deepfake detection, multiple supervision networks are exploited to improve the capability of bi-directional multi-head LSTM to capture spatio-temporal dependencies for strong feature learning.
- Enhanced the robustness and scalability of the models through spatiotemporal optimization techniques to better generalize across different datasets in actual world scenarios.

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